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ABSTRACT

Using Goodman's (1975) notion of quasi-independence as a method of obtaining goodness of fit measures for non-scalable types in a scalogram analysis, archival data sets were examined using available Guttman scaling techniques, recent developments in latent structure analysis, and multidimensional scaling procedures. The Stouffer-Toby (1951) data were reanalyzed using Cloggs' Maximum Likelihood Latent Structure Analysis (MLLSA) and data from Schuman (1970) were reanalyzed using the quasi-independence model. The analysis of data showed that it was possible to extract a two or even higher dimensional solution which can be loosely interpreted. The data failed to produce a coefficient of reproducibility although an alternate goodness of fit measure provided by the model of quasi-independence show these data to define a Guttman scale tolerably well. Results vary widely regarding the Guttman scale depending on what criterion is used to test the data. Given the resultant data discrepancy, it would be unwise to draw conclusions about the adequacy of a Guttman scale on the basis of a single test. Researchers are encouraged towards sequential testing of unidimensionality and convergence of the three methods if Guttman scaling is to remain a meaningful methodological tool. (Author/PN)

Converging Assessments of Unidimensionality

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Abstract

Using Goodman's (1975) notion of quasi-independence as a method of obtaining goodness of fit measures for non-scalable types in a scalogram analysis, archival data sets were examined using available Guttman scaling techniques, recent developments in latent structure analysis, and multidimensional scaling procedures. It was found that alternative methods can yield differing conclusions about the unidimensionality of a scale. Implications in the use of Guttman scaling are discussed. Specifically, researchers are encouraged towards sequential testing of unidimensionality and convergence of the three methods if Guttman scaling is to remain a meaningful methodological tool.

Converging Assessments of Unidimensionality

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A popular and widely used model for scaling dichotomous responses is scalogram analysis or the Guttman scale. A Guttman scale, initially developed by Guttman (cf. Guttman, 1950; Torgerson, 1958), defines a hierarchy of response patterns such that passing an item at the n-th level of the hierarchy implies passing all previous items on the $n - 1$ previous levels. While the vogue of Guttman scaling took place conjointly with the growths in attitude/personality measurement in post-World War II America, it remains a widely used model for scaling response patterns. Developments in the methodology of use of Guttman scales continue to have an active literature (cf. Dawes, 1972).

While scalogram analysis continues to be an actively used data analytic tool, the model is fraught with inherent problems. The most critical of these is its deterministic nature which places severe restrictions on data patterns which can be said to form a Guttman scale. In any data collection, n dichotomous variables can yield possible 2^n responses. Of all these possible responses, only $n + 1$ are allowed by the scalogram model. Typically, responses outside those which define the Guttman scale are obtained. Various goodness (badness) of fit indices have been suggested for evaluation of the applicability of a Guttman scale to data. The most widely known and used is Guttman's own coefficient of reproducibility. The coefficient of reproducibility is the proportion of cells which are perfectly scalable and is defined mathematically as:

$$1 - [\text{no. of errors}/(\#\ \text{respondents})(\#\ \text{items})] \qquad (1)$$

While no strict statistical criterion exists against which a coefficient of reproducibility can be compared, values of 0.9 and greater are assumed to adequately define responses which fit a Guttman scale.

Very early in the history of Guttman scaling, the arbitrary nature of the coefficient of reproducibility was shown. Festinger (1947) gave an example of how the coefficient could be arbitrarily inflated. He further suggested that the assessment of unidimensionality be confined to the rejection of a null hypothesis of unidimensionality rather than an acceptance of the unidimensionality of a given scale.

The coefficient of reproducibility is not the only index which has been suggested in the evaluation of Guttman scales. Other reliability indices are the Kuder-Richardson formula 20 (Kuder & Richardson, 1937) and the Loevinger coefficient of homogeneity (Loevinger, 1947). None of these indices has the property of being compared against some known distribution as a test of a statistical null hypothesis. Instead, the adequacy of a fit for these measures is defined rather loosely in analogy with the Guttman coefficient or Kruskal's stress values in multidimensional scaling (Kruskal, 1964). The methods of assessing fit in Guttman scaling are weaker than the determination of dimensionality from stress values since the one dimensional Guttman solution does not produce the multidimensional scaling analog of the scree test (Cattell, 1966).

While the problem of defining a fit index in the Guttman solution remains unresolved, developments using statistical methods for the Guttman scale have yielded alternative definitions about the adequacy of a Guttman scale to data.

Proctor's (1970) probabilistic formulation of the Guttman scale model is now incorporated into a widely used program for Guttman scaling (SAS, 1979). Various applications of latent structure techniques have also been suggested to better evaluate the adequacy of data to a Guttman scale. Both Proctor's method and the various adaptations of the latent structure model yield chi-square goodness-of-fit tests under maximum likelihood estimation for the adequacy of the Guttman scale to a given set of data. A summary of methods involving various latent structure models is provided in Clogg and Sawyer (Note 3).

Models discussed here relate specifically to the traditional Guttman scaling model and extensions which have been made with regard to this simple one-dimensional model. Multidimensional Guttman scaling, partial order Guttman scaling, and Guttman and Lingoes's Smallest Space Analysis are not considered. A related method of finding the best subset of dichotomous items which can be said to form a Guttman scale has recently been introduced (Price, Dayton, and Macready, 1980).

Latent structure analysis posits the existence of one or more latent unmeasured variables to explain existing relationships between discrete measured variables in contingency tables. While the theoretical conceptualization of the problem has been known for quite some time, it is only recently that efficient computational algorithms have been available for the widespread application of latent structure analysis. Programs currently available include the maximum likelihood programs of Clogg known as MLLSA (Maximum Likelihood Latent Structure Analysis) (Clogg, Note 2; Clogg, 1979) and Haberman's LAT program (Haberman, 1979). A program known as LSA (Latent Structure Analysis) developed by

Mooijaart (Mooijaart, in press) performs latent structure analysis by least squares and generalized least squares.

The idea of analyzing Guttman data by latent structure methods represents a convergence of ideas which were forwarded in the analysis of discrete multivariate data (e.g. Bishop, Fienberg, & Holland, 1975). One such concept is that of structural zeroes. A structural zero is one which occurs in a contingency table (or matrix of responses) which is known a priori to have a zero value. This is distinguished from a sampling zero which occurs due to low relative probability of a cell. An example of a structural zero would be a contingency table cell which defined the number of pregnant males. Such a cell would logically take on a value of zero and could never take on a non-zero value.

The concept of a structural zero was expanded somewhat (Bishop et al., 1975; Goodman, 1975) to consider hypothesis of interest to a researcher where analysis of the complete data would be less meaningful than an analysis which deleted certain cells. For example, in a confusion matrix; a test of interest would not involve a test of independence in the complete table since entries would necessarily be higher along the diagonal (letters being recognized as themselves). Instead, the incomplete table consisting of the matrix with diagonal entries deleted (i.e. taking on a structural zero value) would provide a test of independence among the errors. Such an analysis of an incomplete data matrix for independence among the remaining cells has been called a test of quasi-independence (Bishop et al., 1975).

Goodman (1975) can be said to be responsible for taking the notion of quasi-independence and applying it to latent structure analysis and,

more specifically, to the Guttman scaling problem. In that paper, Goodman proposed the following type of analysis for Guttman type data through the use of latent structure models. Recall that for $\underline{n}$ dichotomously scored items, there are a possible $2^{\underline{n}}$ possible response patterns, $\underline{n} + 1$ of which define the Guttman scale. Goodman proposed the creation of $\underline{n} + 2$ latent classes, $\underline{n} + 1$ latent classes which define those response patterns which are perfectly scalable and an additional latent class to account for response patterns which deviate from a perfect Guttman scale. In this model, the hypothesis of interest is that quasi-independence holds among the deviations from the Guttman scale pattern. This latent class model, if identified, can yield estimates of the probabilities of the latent classes, probabilities of the observed responses conditional on latent class membership, and a likelihood ratio chi square goodness of fit statistic (G^2) which can be used to test the hypothesis of quasi-independence.

The mathematical formulation of the model (from Goodman, 1975) is as follows:

Let p_t = the probability of an individual in latent class $\underline{t}$ $(t = 1,\ldots,n + 2)$

$p_{it}^{\bar{A}}$ = the conditional probability of being at level $\underline{i}$ on variable A given the individual is in the $\underline{t}$-th latent class. Similarly, define $p_{jt}^{\bar{B}}$, $p_{kt}^{\bar{C}}$,... for however many variables there are in the analysis.

$p_{ijk\ldots}^{ABC\ldots}$ = the probability of obtaining response pattern $(i,j,k,\ldots)$

$p_{ijk\ldots t}^{\overline{ABC}}$ = the conditional probability of obtaining response pattern $(i,j,k,\ldots)$ given membership in latent class t.

Then:

$$p_{ijk\ldots}^{\overline{ABC\ldots}} = p_t p_{ijk\ldots}^{ABC} \qquad (2)$$

where responses in the non-scalable class are mutually independent (letting this be class 1, the representation is: $p_{ijk\ldots 1}^{\overline{ABC}\ldots} = p_{i1}^{\overline{A}} p_{j1}^{\overline{B}} \ldots$) and the response patterns for all scalable individuals corresponds to the scale type with probability, 1 e.g. letting class 2 define a response pattern with all negative responses scored zero in the 0-1 dichotomy, $p_{00\ldots 2}^{\overline{AB\ldots}} = 1$.

Goodman (1975) showed applications of the notion of quasi-independence in a Guttman scale by applying the model to some archival data sets. Goodman analyzed these data using his own program with maximum likelihood estimation of model parameters. Here the Stouffer-Toby (1951) data analyzed by Goodman were re-analyzed using Clogg's MLLSA program. Since the estimation procedures are the same in both programs, there should be little difference in the results obtained here compared with Goodman's results. As a second example, data from Suchman (from Coombs, Dawes, & Tversky (1970)) were fit using the quasi-independence model. A similar development has recently been presented by Dayton and Macready (1980) utilizing their own model of hierarchical scaling.

Where a confirmatory hypothesis regarding the Guttman unidimensionality of a scale is of less interest than determining the dimensionality of a scale, other more exploratory techniques may be employed. In particular, use of multidimensional scaling techniques and factor analytic techniques have been used to determine the dimensionality of scales. Here, focus will be placed on multidimensional scaling techniques since dichotomous responses are not appropriately analyzable using traditional exploratory factor analytic techniques although some recent work as been done in the development of models in this area (Muthén, 1978).

<u>Stouffer-Toby (1951) Data</u>

The Stouffer-Toby (1951) data set measuring role conflict on 216 respondents as to whether or not they tend toward universalistic versus particularistic values is a favorite in the latent structure analysis literature and has been a frequently used example (e.g. Goodman, 1974, 1975). Here, as in the subsequent analysis of data from Suchman, only four dichotomous variable are used to demonstrate the model. While the model is equally applicable with $\underline{n}$ variables, the problem of exponential growth in the number of cells in the supermatrix of response patterns makes the four variable problem a computationally simple one.

With four variables, there are 2^4 or 16 possible response patterns. Of these, 4 + 1 or 5 are said to define a Guttman scale i.e. the response patterns (0,0,0,0), (0,0,0,1), (0,0,1,1), (0,1,1,1) and (1,1,1,1) where items are coded such that 1 represents domination of an item. In general, degrees of freedom for the model can be calculated by recalling that there are $2^{\underline{n}}$ data points, $\underline{n} + 1$ possible scale types, and $\underline{n} + 1$ probability parameters which must be estimated for the non-scalable individuals ($\underline{n}$ conditional probabilities and one latent class probability). Therefore, there are $2^{\underline{n}} - 2(\underline{n} + 1)$ degrees of freedom for the general model. For the four variable model in question there are 16 - 10 = 6 degrees of freedom. The choice of a four variable problem was not entirely an arbitrary one by Goodman since $\underline{n}$ must be at least equal to 4 in order for there to be positive degrees of freedom to test a model.

The Stouffer-Toby data were first run on the GUTTMAN SCALE program of the SPSS package. A coefficient of reproducibility of 0.84 was obtained, a value which would have rejected the data as being fit by the Guttman scale model.

A model of quasi-independence was fit to the data with the MLLSA program. The model yielded a likelihood ratio chi-square of 0.99 on six degrees of freedom. Parameter estimates for the latent class and conditional probabilities agreed with those reported by Goodman (1975). While traditional decision rules regarding how well the data fit a Guttman scale would have caused the model to be rejected here, one can see that the errors in the Guttman scale for these data are very well fit by a model of quasi-independence suggesting the retention of the Guttman scale as a model for the data.

Using a generalized least squares solution (Mooijaart, 1981), the proportion of individuals for the unscalable class was estimated to be .682 which agreed well with the maximum likelihood estimate of .68 reported by Goodman (1975). Estimates for the conditional probabilities also corresponded to those in Goodman. The ordinary least squares solution obtained using Mooijaart's LSA 1 program also gave estimates which were consistent with those reported in Goodman (1975).

Another examination of scale unidimensionality was provided by the multidimensional scaling program KYST (Kruskal, Young, & Seery, Note 3). Given that the data actually are unidimensional, a tolerable value of stress in one dimension (Kruskal, 1964) should be obtained. Input to KYST were Yule's Q values which were provided in the SPSS GUTTMAN SCALE procedure. The justification for using this type of input to scaling programs is well established (cf. Kruskal and Wish, 1978).

Here, a stress of 0.230 in one dimension was obtained, a result which, though not good with respect to Kruskal's criterion, represents a more viable solution than the zero stress obtained for these data in two dimensions.

SUCHMAN DATA

The Suchman data taken from Coombs et al., 1970 measured the severity of fear symptoms from soldiers who had been withdrawn from combat during World War II. Items on the scale ranged from "violent pounding of the heart" to "urinating in pants". When one item ("breaking out in a cold sweat") was deleted, the items were said to form a Guttman scale with a coefficient of reproducibility of 0.92 (as reported in Coombs et al., 1970). However, when these data were analyzed independently for the present results, a coefficient of reproducibility of 0.86 was obtained for the full scale of items, a value which, by convention, would have rejected these data as fitting a Guttman scale.

For comparison of the Guttman scale model with the model of quasi-independence, only the four least severe items were considered. As a result the number of total respondents was greatly reduced (from 93 to 44). However, the coefficient of reproducibility of the remaining respondents remained approximately the same as the full data (= .84).

When the model of quasi-independence was run on the MLLSA program[1], a final likelihood ratio chi-square of 4.78 on six degrees of freedom for the model was obtained. This value still represents a statistically significant fit of the model of quasi-independence to the errors in the Guttman scaling of this data.

As with the Stouffer-Toby data, the truncated Suchman data were analyzed to test the hypothesis of unidimensionality using KYST (Kruskal et al., Note 3). A one dimensional stress value of 0.23 was obtained. This value would be considered poor using the Kruskal (1964) criterion. However, the two dimensional solution gave a stress value of zero indicating overfit of the model. Hence, one could potentially conclude

that, while the one dimensional model is not quite adequate according to Kruskal's own rough measures of goodness of fit, it represents an adequate representation of the data which is not guilty of overfitting.

While the quasi-independence model using the latent class formulation becomes computationally burdensome as n increases because of exponential growth in the number of cells in the supermatrix of responses, the KYST model, which involves only a similarity matrix between items, does not becomes quite as laborious with increasing n. Therefore, a test of unidimensionality of the entire Suchman data matrix as reported in Coombs et al., (1970) was performed. Given adequate indices for the unidimensionality of the data, one should have expected the full data matrix to yield a tolerable value of stress in one dimension. The data were tested in both one and two dimensions.

In the one dimensional solution of the full Suchman data, a stress value of .301 was obtained. The two dimensional solution gave a stress value of .151. While neither of these values would represent good fits by the Kruskal (1964) criterion, it seems rather apparent that the two dimensional solution is better than the one dimensional solution. The three dimensional solution has even better stress value (0.05). It, however, lacks the rough interpretability which can be made in the two dimensional solution.

In looking at the two dimensional solution, it appears that all items which load negatively on the first dimension (with the exception of the "urine" item) seem to reflect covert cognitive manifestations of fear (e.g. "a sinking feeling of the stomach") versus overt physiological manifestations of fear (e.g. "vomiting").

The second dimension, while not as easily interpretable as the first, seems to reflect the degrees of control which could be exercised over the manifestations of the fear symptoms ranging from a perception of possibly high control (e.g. "feeling of stiffness") to perceptions of little or no control ("violent pounding of the heart").

Insert Table 1 About Here

DISCUSSION

Analysis of the Suchman data has provided a strong example of the pratfalls of Guttman scaling. These data showed that: a) it wass possible to extract a two or even higher dimensional solution which can be loosely interpreted; and b) even if one could accept a one dimensional solution as being tolerable for this data set, the data failed to meet the traditionally established and well-known criterion of producing a coefficient of reproducibility of 0.9 or greater although an alternate goodness of fit measure provided by the model of quasi-independence show these data to define a Guttman scale tolerably well. Results here have clearly shown that widely varying conclusions regarding the adequacy of a Guttman scale to a given data set may be reached depending on what criterion is used to test the data.

Given the inherent difficulty with scalogram analysis, the question arises as to whether or not the method can be justifiably retained to perform meaningful types of scaling. The best way of assessing the adequacy of the scalogram model would be to perform sequential tests on the same data set. One could perform the traditional scalogram analysis such as the one found in the SPSS or SAS packages, a test of quasi-

independence of the errors in a Guttman scale using either latent class or log-linear models, and a comparison of a unidimensional solution and multidimensional solutions in a multidimensional scaling program such as KYST.

Using the ideas of sequential testing for unidimensionality takes a procedure which could be done manually and evolves it into a time-consuming and potentially expensive computational procedure. In addition, both the latent class and multidimensional scaling analyses have theoretical problems in convergence (local versus global minima) which make these individual procedures potentially prohibitive both in cost and time. However, given the discrepancy in the results shown here with the same set of data, it would be unwise to conclude on the adequacy of a Guttman scale on the basis of any single test.

On the other hand, it is debatable whether much is gained through the use of sequential testing. For any real set of items which are thought to form a Guttman scale, the number of items n is too large to create the supermatrix of response patterns which can be handled with any computational efficiency for the statistically based models. Even if computational algorithms did exist which could handle an infinitely large supermatrix of response patterns, the number of subjects N needed such that the majority of entries in the supermatrix was not zero would be prohibitive. Hence, the strongest criterion for determination of the adequacy of a Guttman scale can, in fact, be used only the most restrictive of conditions (n no greater than 6 or 7 at the most).

Guttman scales, and indeed much of scaling, is fraught with problems in the interpretation of dimensionality. Currently, this problem is resolved in multidimensional scaling by eyeballing scree plots,

comparing obtained stress values against stress values of random data from Monte Carlo studies, or an even looser "good - poor" index (Kruskal, 1964). No strict statistical criterion has yet been developed against which these particular indices of fit may be compared. Given this flexibility in interpretation and the fact that a researcher usually enters with a hypothesis of the dimensionality he/she wishes to find, it is probably too tempting for the researcher to reject as non-significant the n + 1 dimensions greater than the n he/she wanted to extract. This becomes particularly relevant in a Guttman scale analysis since the researcher looking for a unidimensional phenomenon can bias his/her efforts in finding a unidimensional phenomenon unless all indices for the goodness of fit for the data are simply intolerable. Of course, since the researcher is looking for a unidimensional phenomenon, he/she will tend to construct scales which reflect the hypothesis of unidimensionality resulting in rare rejection of the null hypothesis. It seems, in retrospect, that Festinger's (1947) approach to the unidimensionality of a scale was correct.

While Guttman scaling provides an efficient way of summarizing data, researchers interested in hypotheses of unidimensionality should carefully assess the methods they use in testing their hypotheses. As was seen clearly in the Suchman data, alternative methods of assessing unidimensionality can yield contradictory results. Careful scrutiny of Guttman scalable data is necessary prior to drawing conclusions regarding the scalability of any given data set.

Footnotes

[1]While the number of respondents in the truncated Guttman scale analysis was 44, a value of 1.0 was added to all zero cells for the MLLSA analysis because of problems in the estimation of parameters with cells which contained zero entries. This is a well-known (and hotly debated) technique in contingency table analysis (see Fienberg, 1977 or Dixon, 1977 on the estimation of log-linear models in the BMD package).

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Table 1

Two Dimensional Solution of Suchman Data

after Principal Components Rotation

Item label	1	2
1. Violent pounding of the heart	.496	-1.390
2. Sinking feeling of the stomach	-1.418	.100
3. Shaking or trembling all over	-.616	-.621
4. Feeling sick at the stomach	.129	.055
5. Feeling of stiffness	.068	.845
6. Feeling of weakness or feeling faint	-.507	.628
7. Vomiting	1.048	.853
8. Losing control of the bowels	.861	-.218
9. Urinating in pants	-.061	-.233